Food Reviews Sentiment Analysis & Recommendation System

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Introduction

I will be attempting to improve upon the Amazon Fine Food Reviews SA and recommendation system given as an example in class, with different settings and methods. We will be using the 'Amazon Fine Food Review' from Kaggle at

[https://www.kaggle.com/datasets/snap/amazon-fine-food-reviews (https://www.kaggle.com/datasets/snap/amazon-fine-food-reviews)](https://www.kaggle.com/datasets/snap/amazon-fine-food-reviews)

Using the reviews, we will use a RNN with LSTM to perform Sentiment Analysis on the reviews. We will then use a Restricted Boltzmann Machine (RBM) using tensorflow v1 to make a recommendation system.

Let's start by loading the libraries and dataset.

In [ ]:

```
# Utilities
import pandas as pd
import datetime
import re

# Visualization
from matplotlib import pyplot as plt
import numpy as np
import seaborn as sns

# ML DL
import keras
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.preprocessing import sequence
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Dense, LSTM, Embedding, Dropout
from tensorflow.keras.models import Sequential

# NLP stopwords
from keras.preprocessing.text import Tokenizer
from nltk.corpus import stopwords
from string import punctuation
```

In [2]:

```
# turn warnings off
import warnings
warnings.filterwarnings("ignore")
```

In [4]:

```
# Import the data set
df = pd.read_csv('datasets/Reviews.csv')
df.head()
```

Out[4]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d...
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a fe...
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine	If you are looking for the secret ingredient i...
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy	Great taffy at a great price. There was a wid...

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 568454 entries, 0 to 568453
Data columns (total 10 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   Id                      568454 non-null  int64
 1   ProductId               568454 non-null  object
 2   UserId                  568454 non-null  object
 3   ProfileName             568438 non-null  object
 4   HelpfulnessNumerator    568454 non-null  int64
 5   HelpfulnessDenominator  568454 non-null  int64
 6   Score                   568454 non-null  int64
 7   Time                    568454 non-null  int64
 8   Summary                 568427 non-null  object
 9   Text                    568454 non-null  object
dtypes: int64(5), object(5)
memory usage: 43.4+ MB
```

It looks like there are over half a million reviews, but our processing power will not make this feasible, so I will be taking the first 24k reviews in honor of Kobe Bryant.

In [7]:
```
df = df[0:24000] # only using the first 24,000 reviews
```

Now we will grab only the columns we need. We will take ProductId so we know the product, ProfileName so we know the reviewer, Score so we know what they scored, Summary for displaying at end, Text for the actual review for SA and recommendation, and the two Helpfulness columns to rate helpfulness.

In [8]:
```
# save needed columns in new df
df_reviews = df[['ProductId','ProfileName','Score','Summary','Text','HelpfulnessNumerator','HelpfulnessDenominator']]
```

Now let's get familiar with our most active reviewers.

In [9]:
```
# Display the top 10 Reviewers by most reviews.
df.pivot_table(columns=['ProfileName'], aggfunc='size').sort_values(ascending=False).head(10)
```

Out[9]:
```
ProfileName
c2                                          24
Chris                                       19
C. F. Hill "CFH"                            17
Carrie, "Formerly &#34;Sister Carrie&#34;"  17
Gary Peterson                               17
John                                        15
Dan                                         15
Sharon                                      12
Bill                                        12
O. Brown "Ms. O. Khannah-Brown"             12
dtype: int64
```

It looks like c2 is our most active reviewer with 24 reviews, followed by Chris with 19, and then the others.

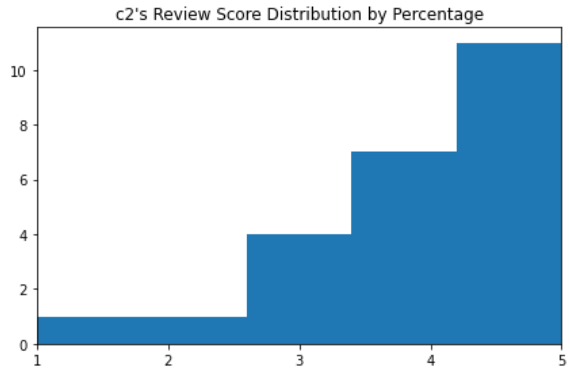
Let's explore our top reviewer, c2, a little more in depth.

In [13]:
```
#Filtering all the reviews made by user c2
c2_reviews = df_reviews[df_reviews['ProfileName']=='c2']
c2_reviews
```

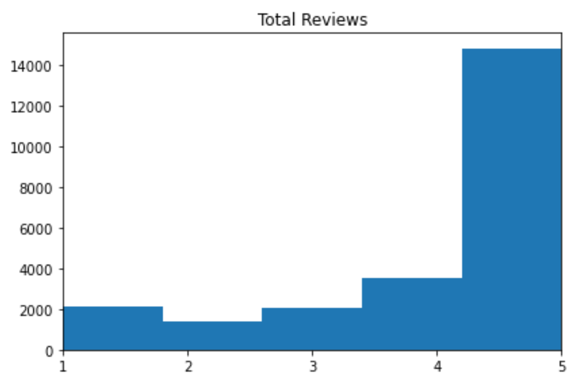
Out[13]:

	ProductId	ProfileName	Score	Summary	Text	HelpfulnessNumerator	HelpfulnessDenominator
143	B001GVISJW	c2	5	Great for the kids!	If you are looking for a less messy version of...	0	0
3587	B004X8TK9W	c2	5	AWESOME!	I may be dating myself here a bit but I rememb...	1	1
4993	B000FA398U	c2	5	Best for oyster soup!	Try these first for all your seafood soups and...	3	3
6371	B000084EKO	c2	3	Not any different than regular Friskies	I honestly cannot say that I saw any differenc...	0	0
6372	B000084EKA	c2	4	Not their best...	I think 9 Lives does a better job on this vari...	0	0
6373	B000084EKB	c2	4	Great food!	This version is ground. NOt my current cat's ...	0	0
6374	B000084EKC	c2	5	Great food for all cats!	According to my cat, this stuff is just great....	1	1
6375	B000084EKD	c2	2	Needs improved	I haven't had a cat yet that liked this one. ...	1	1
6380	B000084EKG	c2	5	Awesome food!	This is my cat's favorite one. He just licks ...	2	2
6382	B000084EK8	c2	3	Not the favorite in our house	Once or twice a year for a little variety and ...	2	2
6385	B000084EK9	c2	1	This stuff is bad!	I honestly have to say that I just won't buy t...	0	0
6393	B000084EK4	c2	3	Great beef look	This food variety is ground, thus my cat doesn...	0	0
6394	B000084EK5	c2	5	Family favorite - looks like steak!	This is my cat's third favorite food. It's gr...	1	1
6395	B000084EK6	c2	5	Great food!	This is another favorite in our house. My cat...	0	0
6396	B000084EK7	c2	4	What's in this?	This one is a great basic food. Whatever is in...	0	0
8028	B0012KH06Y	c2	3	Great nutrition...	These guys are quite high on the nutritional s...	2	2
8222	B000BXUVYG	c2	4	Nice treat, make sure they CHEW them!	As with most cats I've read about here, both o...	1	1
11068	B004INIUQQ	c2	5	Loved by one, hated by the other	This is a new line for Friskies and is not a "...	0	0
11776	B0012KB4WU	c2	4	Best of the florentines	This one seems to be flavored more to a cat's ...	3	3
16441	B007TJGZ54	c2	4	Not the best, but CERTAINLY, not the worst!	This is a breakfast blend coffee and, for many...	0	0
19062	B001FA1EZ4	c2	5	Super yum!	I just love Hershey's chocolate anyway, so it'...	2	2
19965	B001G0NKVO	c2	5	Great starter for this variety	In case you're wondering, this is a pate, and ...	3	3
22608	B002CJAOTY	c2	5	Great food, very meaty smelling and appetizing	My salmon loving Persian thinks this is her se...	0	0
23077	B004ZIER34	c2	4	LOVE the low acid, quite strong, however	Overall, if you're looking for a low-acid, "he...	0	0

In [14]:
```
fig, axs = plt.subplots(sharey=True, tight_layout=True)
axs.hist(c2_reviews['Score'],bins=5)
plt.xlim([1, 5])
plt.xticks(np.arange(1, 6, 1))
plt.title("c2's Review Score Distribution by Percentage")
plt.show()
```



In [15]:
```
fig, axs = plt.subplots(sharey=True, tight_layout=True)
axs.hist(df_reviews['Score'],bins=5)
plt.xlim([1, 5])
plt.xticks(np.arange(1, 6, 1))
plt.title('Total Reviews')
plt.show()
```



As we can see, there is a bit more of a curve to c2's distribution compared to all the reviews. We can also see c2's reviews has Helpfulness scores, indicating other users found c2's reviews helpful. Good job c2, you're a model reviewer!

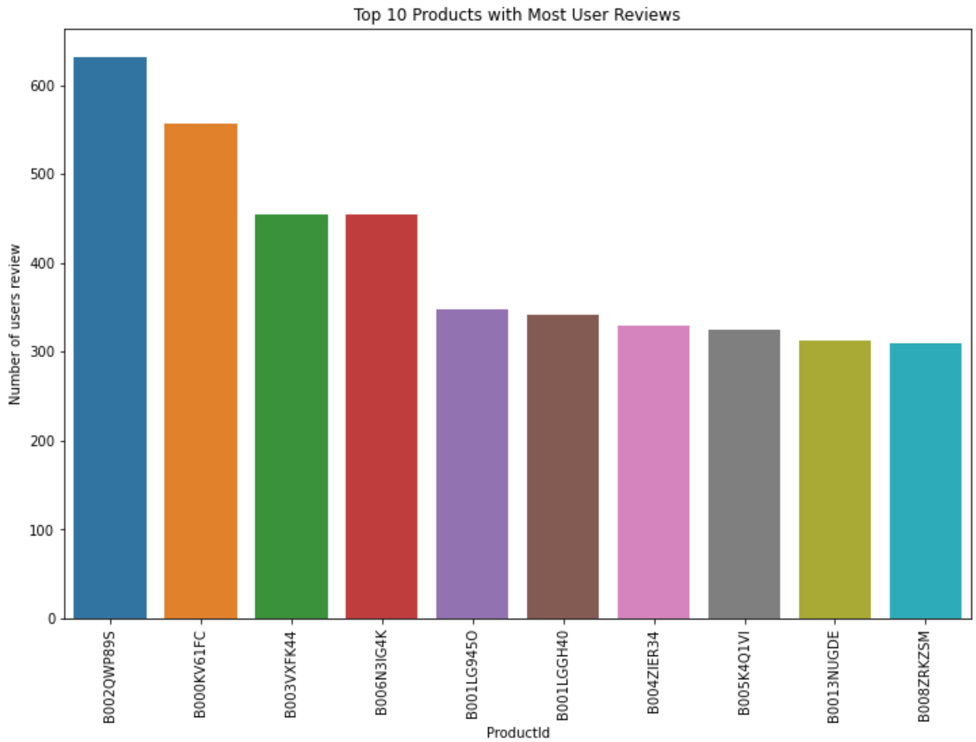
Now let's check out the top 10 products with the most reviews.

In [10]:
```
# Display the top 10 products by most reviews.
df.pivot_table(columns=['ProductId'], aggfunc='size').sort_values(ascending=False).head(10)
```

Out[10]:
```
ProductId
B002QWP89S    632
B000KV61FC    556
B003VXFK44    455
B006N3IG4K    455
B001LG945O    347
B001LGGH40    341
B004ZIER34    330
B005K4Q1VI    324
B0013NUGDE    312
B008ZRKZSM    310
dtype: int64
```

In [11]:
```
top = df[['ProductId', 'ProfileName']].groupby('ProductId').agg({'ProfileName':'count'}) # create aggregated df with count
p = top.sort_values('ProfileName', ascending = False).head(10) # sort the values based of number of users count
plt.figure(figsize = (12,8)) # set size of figure to display
sns.barplot(x = p.index, y = p.ProfileName, order=p.index) # display barplot using index as the order and the count as y
plt.xticks(rotation = 90) # rotate ProductId for easier viewing
plt.title('Top 10 Products with Most User Reviews')
plt.ylabel('Number of users review')
```

Out[11]: Text(0, 0.5, 'Number of users review')



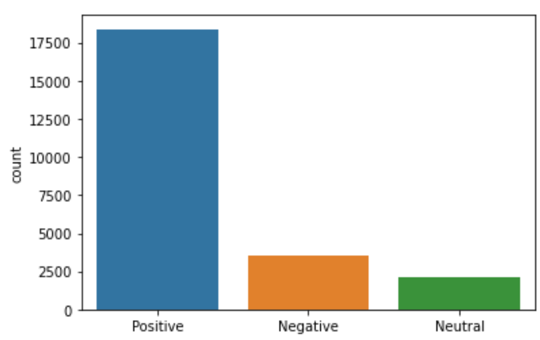
We can see the distribution and number of reviews for the top 10 products, but unfortunately this dataset does not contain the name of the product, only the productID number, so we can only guess what all the rave is about.

Next, we are going to create a new column with the polarity, where if the score scores of 4 or 5 is positive, 3 is neutral, and less than 3 is negative.

In [24]:
```
df_reviews['Polarity_Rating'] = df_reviews['Score'].apply(lambda x: 'Positive' if x > 3 else x)
df_reviews['Polarity_Rating'] = df_reviews['Polarity_Rating'].apply(lambda x: 'Neutral' if isinstance(x, int) and x ==3 els
df_reviews['Polarity_Rating'] = df_reviews['Polarity_Rating'].apply(lambda x: 'Negative' if isinstance(x, int) and x < 3 el
```

In [25]:
```
sns.countplot(data = df_reviews, x= 'Polarity_Rating')
```

Out[25]: <AxesSubplot:xlabel='Polarity_Rating', ylabel='count'>



In [29]:
```
df_reviews[df_reviews['Polarity_Rating'] == 'Positive'].shape[0]
```

Out[29]: 18375

In [26]:
```
df_reviews[df_reviews['Polarity_Rating'] == 'Negative'].shape[0]
```

Out[26]: 3542

In [27]:
```
df_reviews[df_reviews['Polarity_Rating'] == 'Neutral'].shape[0]
```

Out[27]: 2083

It looks like there are a lot more positive reviews, so we are going to make a balanced df where the number of positive and negative reviews match, but we will keep the neutral the same slightly lower than the others, since neutral represents only the score 3 where as positive and negative each represent 2 scores.

In [31]:
```
data_Positive = df_reviews[df_reviews['Polarity_Rating'] == 'Positive'][0:3542]
data_Negative = df_reviews[df_reviews['Polarity_Rating'] == 'Negative']
data_Neutral = df_reviews[df_reviews['Polarity_Rating'] == 'Neutral']

data_Negative_over = data_Negative.sample(8000, replace=True)
df_balance_reviews = pd.concat([data_Positive, data_Neutral, data_Negative_over], axis=0)
```

Data Cleaning

We will clean the data. We will set the actual reviews as x_data, and the polarity rating as the y_data. We then clean the x_data, taking out html tags, anything not a letter, stopwords, and making everything lower case.

We will also replace Positive with 1, and both Negative and Neutral with 0, in the y_data. Even though this skews our data more towards negative, this is done because sigmoid output is more efficient and is best with 1 neuron, where output is logistic. Otherwise we could try tanh function with 3 output neurons, but that would be more tuning hyperparameters.

In [32]:
```
# Setting the stop words
english_stops = set(stopwords.words('english'))
```

In [69]:
```
df = df_balance_reviews # copy df
x_data = df['Text']       # Reviews/Input as x_data
y_data = df['Polarity_Rating']    # Sentiment/Output as y_data

# PRE-PROCESS REVIEW
x_data = x_data.replace({'<.*?>': ''}, regex = True)          # remove html tag
x_data = x_data.replace({'[^A-Za-z]': ' '}, regex = True)     # remove non alphabet
x_data = x_data.apply(lambda review: [w for w in review.split() if w not in english_stops])  # remove stop words
x_data = x_data.apply(lambda review: [w.lower() for w in review])   # lower case

# ENCODE SENTIMENT -> 0 & 1
y_data = y_data.replace('Positive', 1)
y_data = y_data.replace('Neutral', 0)
y_data = y_data.replace('Negative', 0)
```

LSTM RNN

Let's continue preparing the data for a RNN with LSTM (Long-Short-Term Memory). We will split the data into train and test sets, and make a function to get the maximum length of the reviews, for padding later.

In [70]:
```
# split data into train test, 20% test size, random_state=42
X_train, X_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.2, random_state=42)
```

In [71]:
```
# function to get max length of reviews for padding
def get_max_length(x_train):
    review_length = []
    for review in x_train:
        review_length.append(len(review))

    return int(np.ceil(np.mean(review_length)))
```

In [72]:
```
max_length = get_max_length(X_train)
print(max_length)
```

```
49
```

Now that we have the max length of the reviews, we will encode it by tokenizing the reviews, then turning it into a sequence before padding the sequence to the max length.

In [73]:

```
# ENCODE REVIEW
token = Tokenizer(lower=False)    # False becuase we already did it.
token.fit_on_texts(X_train) # tokenize X_train
x_train = token.texts_to_sequences(X_train) # encode to sequence
x_test = token.texts_to_sequences(X_test) # encode x_test to sequence

### add the pad to x_train
x_train = pad_sequences(x_train, maxlen=max_length, padding='post', truncating='post')

### add pad to x_test
x_test = pad_sequences(x_test, maxlen=max_length, padding='post', truncating='post')

total_words = len(token.word_index) + 1   # we need to add 1 because of 0 padding
```

RNN with LSTM

It's time to build the RNN with LSTM. We start with the embed dimensions, where each dimension can learn a feature. We will use 3200 because it is a high number that should get any features we have.

Next we instantiate a sequential model, and add embedding layer before the LSTM layer. We then add a 20% dropout layer to help against overfitting, before having a Dense output layer with 1 neuron with sigmoid activation, so it will be either a score between 0 and 1, for negative to positive. We then compile with adam optimizer and binary_crossentropy as the loss function.

We will also create a checkpoint to save progress on completed epochs.

In [74]:

```
# RNN LSTM ARCHITECTURE
EMBED_DIM = 3200
LSTM_OUT = 64

# Instantiate a sequential model
model = Sequential()

#model.add(Embedding(input_dim=max_length, output_dim=LSTM_OUT,input_length=max_length))
model.add(Embedding(total_words, EMBED_DIM, input_length = max_length))
model.add(LSTM(LSTM_OUT)) # LSTM layer
model.add(Dropout(0.2)) # dropout to help against overfitting
model.add(Dense(units=1, activation='sigmoid'))

### compile the model using: optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy']
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

#Adding a Checkpoint to save the model.
checkpoint = ModelCheckpoint('models/LSTM.h5', monitor='accuracy', save_best_only=True, verbose=1)
```

In [75]:

```
model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_6 (Embedding)     (None, 49, 3200)          55430400

 lstm_6 (LSTM)               (None, 64)                835840

 dense_6 (Dense)             (None, 1)                 65

=================================================================
Total params: 56266305 (214.64 MB)
Trainable params: 56266305 (214.64 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Time to fit the model. We will use 8 epochs in other of Kobe's other retired jersey.

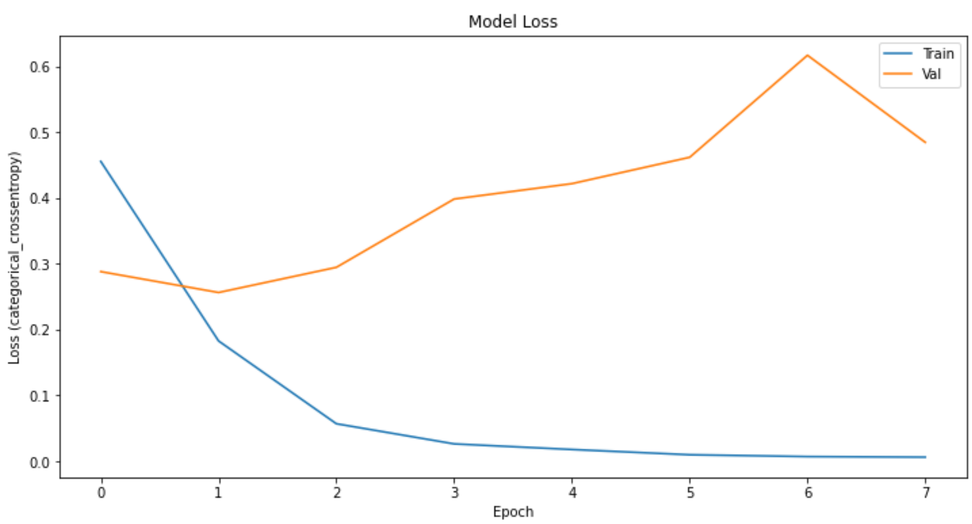
In [76]:
```
history = model.fit(x_train, y_train, epochs=8, batch_size=20, callbacks= [checkpoint],validation_data=(x_test, y_test))
```

```
545/545 [==============================] - ETA: 0s - loss: 0.4557 - accuracy: 0.7951
Epoch 1: accuracy improved from -inf to 0.79514, saving model to models\LSTM.h5
545/545 [==============================] - 367s 671ms/step - loss: 0.4557 - accuracy: 0.7951 - val_loss: 0.2882 - val_a
ccuracy: 0.8855
Epoch 2/8
545/545 [==============================] - ETA: 0s - loss: 0.1829 - accuracy: 0.9311
Epoch 2: accuracy improved from 0.79514 to 0.93110, saving model to models\LSTM.h5
545/545 [==============================] - 380s 698ms/step - loss: 0.1829 - accuracy: 0.9311 - val_loss: 0.2565 - val_a
ccuracy: 0.9090
Epoch 3/8
545/545 [==============================] - ETA: 0s - loss: 0.0571 - accuracy: 0.9821
Epoch 3: accuracy improved from 0.93110 to 0.98211, saving model to models\LSTM.h5
545/545 [==============================] - 367s 674ms/step - loss: 0.0571 - accuracy: 0.9821 - val_loss: 0.2948 - val_a
ccuracy: 0.9057
Epoch 4/8
545/545 [==============================] - ETA: 0s - loss: 0.0264 - accuracy: 0.9919
Epoch 4: accuracy improved from 0.98211 to 0.99193, saving model to models\LSTM.h5
545/545 [==============================] - 373s 684ms/step - loss: 0.0264 - accuracy: 0.9919 - val_loss: 0.3986 - val_a
ccuracy: 0.9020
```

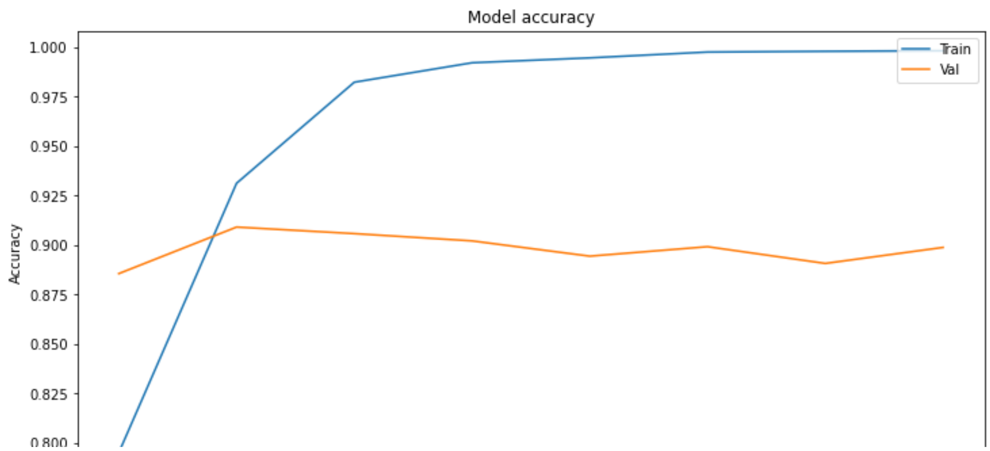
Now let's plot the loss and accuracy to analyze how the model did.

In [77]:
```
plt.figure(figsize=(12,6))
plt.plot(model.history.history['loss'][:])
plt.plot(model.history.history['val_loss'][:])
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss (categorical_crossentropy)')
plt.legend(['Train', 'Val'], loc='upper right')
```

Out[77]: `<matplotlib.legend.Legend at 0x241095894c0>`



In [78]:
```
plt.figure(figsize=(12,6))
plt.plot(model.history.history['accuracy'][:])
plt.plot(model.history.history['val_accuracy'][:])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()
```



It looks like although the accuracy was surprisingly high, the loss on test set was going up before barely starting to drop again. We may have been in a local minima before breaking out. I really should of went with Kobe's 24 jersey for epochs instead of 8, but I was afraid of the process time.

Predicting Sentiment

Now let's have some fun. We will grab a random review, clean the review, encode it, then make a prediction based on the model we fit. Let's pick index 2020, for the year Kobe died, so not completely random, but random in the context of the data.

In [79]:
```
#I grab a random review from the dataframe
value = 2020
df_reviews.iloc[value]
```

Out[79]:
```
ProductId                                                B001E5E29A
ProfileName                                              FPU "Dave"
Score                                                             5
Summary                                          Farmhouse Waffle Mix
Text                      Makes very good, light waffles. Seems to be ex...
HelpfulnessNumerator                                              1
HelpfulnessDenominator                                            1
Polarity_Rating                                            Positive
Name: 2020, dtype: object
```

In [80]:
```
review = df_reviews.iloc[value]['Text']
print(review)
```

Out[80]:
```
"Makes very good, light waffles. Seems to be exactly the same as Carbon's Golden Malted waffle mix. Only this is more expe
nsive."
```

In [81]:
```
# clean data
regex = re.compile(r'[^a-zA-Z\s]') # make patern for letters only
review = regex.sub('', review) # replace non letters with no space

words = review.split(' ') # split words into list
filtered = [w for w in words if w not in english_stops] # take out stopwords
filtered = ' '.join(filtered) # join list
filtered = [filtered.lower()] # lower case
```

In [82]:
```
tokenize_words = token.texts_to_sequences(filtered) # tokenize words to sequences
tokenize_words = pad_sequences(tokenize_words, maxlen=max_length, padding='post', truncating='post') # pad sequences
```

In [83]:
```
result = model.predict(tokenize_words)

if result >= .50:
    print('Postive')
else:
    print('Negative')
```

```
1/1 [==============================] - 2s 2s/step
Postive
```

That worked great. Reading the review, it sounded mostly positive besides the comment on the price, but had a score of 5 so it was definitely positive.

Let's make a function that will take in a number, and print the corresponding summary and review, along with prediction whether it is positive or negative.

In [86]:
```
def predict_sentiment(value):
    review = df_reviews.iloc[value]['Text']
    summary = df_reviews.iloc[value]['Summary']
    score = df_reviews.iloc[value]['Score']
    regex = re.compile(r'[^a-zA-Z\s]')
    review = regex.sub('', review)

    words = review.split(' ')
    filtered = [w for w in words if w not in english_stops]
    filtered = ' '.join(filtered)
    filtered = [filtered.lower()]
    tokenize_words = token.texts_to_sequences(filtered)
    tokenize_words = pad_sequences(tokenize_words, maxlen=max_length, padding='post', truncating='post')
    result = model.predict(tokenize_words)
    print(f'Review Index: {value}')
    print(f'Review Summary: {summary}')
    print(f'Review Text: {review}')
    if result >= .50:
        print('Prediction of Sentiment is: Postive')
        print(f'Sentiment Score Prediction: {result}')
        print(f'Actual Review Score: {score}')

    else:
        print('Prediction of Sentiment is: Negative')
        print(f'Sentiment Score Prediction: {result}')
        print(f'Actual Review Score: {score}')
```

In [87]:
```
predict_sentiment(2023)
```

```
1/1 [==============================] - 0s 32ms/step
Review Index: 2023
Review Summary: Excellent choice for Belgian Waffles
Review Text: I have a Waring belgian waffle maker and was looking for a good batter to use I tried this based on reviews a
nd with add my strong recommendation for this mixbr br It was very easy to make and the waffles had a wonderful flavor  lo
ved the malt flavor that came throughbr br I will definitely be buying more when the current mix runs out
Prediction of Sentiment is: Postive
Sentiment Score Prediction: [[0.99933594]]
Actual Review Score: 5
```

The function seems to work good.

RBM

Now let's prep the data for the RBM. We will start by giving each user or ProfileName a unique UserID using pandas.factorize()

After that, we will find the UserID of our top reviewer, c2.

In [88]:
```
#Making an Unique Numeric ID for all the users
df_reviews['UserID'] = pd.factorize(df_reviews['ProfileName'])[0] + 1
```

In [89]:
```
df_reviews[df_reviews['ProfileName'] == 'c2'].head()
```

Out[89]:

	ProductId	ProfileName	Score	Summary	Text	HelpfulnessNumerator	HelpfulnessDenominator	Polarity_Rating	UserID
143	B001GVISJW	c2	5	Great for the kids!	If you are looking for a less messy version of...	0	0	Positive	143
3587	B004X8TK9W	c2	5	AWESOME!	I may be dating myself here a bit but I rememb...	1	1	Positive	143
4993	B000FA398U	c2	5	Best for oyster soup!	Try these first for all your seafood soups and...	3	3	Positive	143
6371	B000084EKO	c2	3	Not any different than regular Friskies	I honestly cannot say that I saw any differenc...	0	0	Neutral	143
6372	B000084EKA	c2	4	Not their best...	I think 9 Lives does a better job on this vari...	0	0	Positive	143

c2 has been given UserID 143, 'I love you'.

In [90]:
```
df_reviews[df_reviews['UserID'] == 143].head()
```

Out[90]:

	ProductId	ProfileName	Score	Summary	Text	HelpfulnessNumerator	HelpfulnessDenominator	Polarity_Rating	UserID
143	B001GVISJW	c2	5	Great for the kids!	If you are looking for a less messy version of...	0	0	Positive	143
3587	B004X8TK9W	c2	5	AWESOME!	I may be dating myself here a bit but I rememb...	1	1	Positive	143
4993	B000FA398U	c2	5	Best for oyster soup!	Try these first for all your seafood soups and...	3	3	Positive	143
6371	B000084EKO	c2	3	Not any different than regular Friskies	I honestly cannot say that I saw any differenc...	0	0	Neutral	143
6372	B000084EKA	c2	4	Not their best...	I think 9 Lives does a better job on this vari...	0	0	Positive	143

Further cleaning

We will clean data one more time to drop multiple reviews of product from the same user. We will drop duplicates and only keep the last follow up review rather than all the reviews.

In [92]:
```
# clean the data some more, some reviewers went back to review the same item mulitple times as a follow up.
cleaned = df_reviews.drop_duplicates(subset=['ProductId', 'UserID'], keep='last')

print('Total Reviews: {}'.format(df_reviews.shape[0]))
print('Removed Dulipcated, Total Reviews Left: {}'.format(cleaned.shape[0]))
```

```
Total Reviews: 24000
Removed Dulipcated, Total Reviews Left: 23641
```

In [93]:
```
cleaned.head()
```

Out[93]:

	ProductId	ProfileName	Score	Summary	Text	HelpfulnessNumerator	HelpfulnessDenominator	Polarity_Rating	UserID
0	B001E4KFG0	delmartian	5	Good Quality Dog Food	I have bought several of the Vitality canned d...	1	1	Positive	1
1	B00813GRG4	dll pa	1	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...	0	0	Negative	2
2	B000LQOCH0	Natalia Corres "Natalia Corres"	4	"Delight" says it all	This is a confection that has been around a fe...	1	1	Positive	3
3	B000UA0QIQ	Karl	2	Cough Medicine	If you are looking for the secret ingredient i...	3	3	Negative	4
4	B006K2ZZ7K	Michael D. Bigham "M. Wassir"	5	Great taffy	Great taffy at a great price. There was a wid...	0	0	Positive	5

Now we need to make a pivot table where the UserID is the index, each column is a ProductId, and the values are the scores.

In [94]:
```
user_rating_df = cleaned.pivot(index='UserID', columns='ProductId', values='Score') # create pivot table
```

In [95]:
```
user_rating_df.head()
```

Out[95]:

ProductId	B00002NCJC	B00002Z754	B00005V3DC	B000084DVR	B000084E1U	B000084EK4	B000084EK5	B000084EK6	B000084EK7	B000084EK8	...	E
UserID												
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	
5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	

5 rows × 2987 columns

RBM with Tensorflow v1

This RBM is made with Tensorflow v1, so disable eager execution. Then we normalize the data by filling all the na with 0 before dividing each value by 5 for the 5 different scores. Save to array trX

In [96]:
```
tf.compat.v1.disable_eager_execution() # disable eager execution for v1
```

In [97]:
```
norm_user_rating_df = user_rating_df.fillna(0) / 5.0 # normalize by fillna with 0, diving each value by 5 for each score
trX = norm_user_rating_df.values # create array with the values
trX[0:5]
```

Out[97]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

Here is the actual RBM. We will first initialize the weights and visible states and hidden states to variables before going through the forward pass or phase 1, where the positive and negative associations are learned. Those associations are saved, before phase 2 reconstruction occurs, and the weights are adjusted in the backward pass.

Lastly we will run a loop that will run through each epoch, printing the error for each epoch. To keep with the Kobe love, we will use 24 epochs.

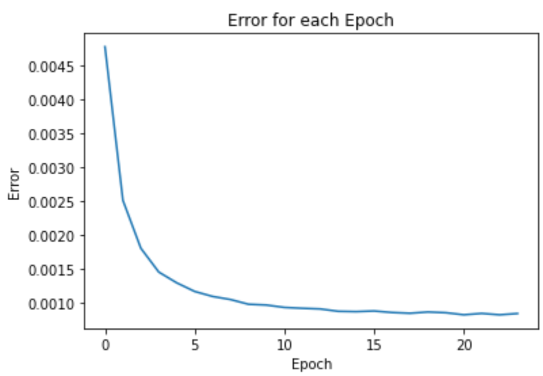
In [99]:

```
hiddenUnits = 20
visibleUnits =  len(user_rating_df.columns)
vb = tf.compat.v1.placeholder("float", [visibleUnits])
hb = tf.compat.v1.placeholder("float", [hiddenUnits])
W = tf.compat.v1.placeholder("float", [visibleUnits, hiddenUnits])

# Process phase 1 of a RBM, use v0, _h0, h0
v0 = tf.compat.v1.placeholder("float", [None, visibleUnits])
_h0 = tf.nn.sigmoid(tf.matmul(v0, W) + hb)
h0 = tf.nn.relu(tf.sign(_h0 - tf.random.uniform(tf.shape(input=_h0))))

#Phase 2: Reconstruction
_v1 = tf.nn.sigmoid(tf.matmul(h0, tf.transpose(W)) + vb)
v1 = tf.nn.relu(tf.sign(_v1 - tf.random.uniform(tf.shape(input=_v1))))
h1 = tf.nn.sigmoid(tf.matmul(v1, W) + hb)

#Learning rate
alpha = 1.0

w_pos_grad = tf.matmul(tf.transpose(v0), h0)
w_neg_grad = tf.matmul(tf.transpose(v1), h1)

CD = (w_pos_grad - w_neg_grad) / tf.compat.v1.to_float(tf.shape(v0)[0])

update_w = W + alpha * CD
update_vb = vb + alpha * tf.reduce_mean(v0 - v1, 0)
update_hb = hb + alpha * tf.reduce_mean(h0 - h1, 0)

err = v0 - v1
err_sum = tf.reduce_mean(err * err)

#Current weight
cur_w = np.zeros([visibleUnits, hiddenUnits], np.float32)

cur_vb = np.zeros([visibleUnits], np.float32)

cur_hb = np.zeros([hiddenUnits], np.float32)

prv_w = np.zeros([visibleUnits, hiddenUnits], np.float32)

prv_vb = np.zeros([visibleUnits], np.float32)

prv_hb = np.zeros([hiddenUnits], np.float32)

sess = tf.compat.v1.Session()
sess.run(tf.compat.v1.global_variables_initializer())


# Using a for loop, Run the model, with 24 epochs (go Kobe!), batchsize = 100, and errors = []
epochs = 24
batchsize = 100
errors = []
for i in range(epochs):
    for start, end in zip( range(0, len(trX), batchsize), range(batchsize, len(trX), batchsize)):
        batch = trX[start:end]
        cur_w = sess.run(update_w, feed_dict={v0: batch, W: prv_w, vb: prv_vb, hb: prv_hb})
        cur_vb = sess.run(update_vb, feed_dict={v0: batch, W: prv_w, vb: prv_vb, hb: prv_hb})
        cur_nb = sess.run(update_hb, feed_dict={v0: batch, W: prv_w, vb: prv_vb, hb: prv_hb})
        prv_w = cur_w
        prv_vb = cur_vb
        prv_hb = cur_hb
    errors.append(sess.run(err_sum, feed_dict={v0: trX, W: cur_w, vb: cur_vb, hb: cur_hb}))
    print (f'Epoch: {i+1} == Error: {errors[-1]}')
```

```
Epoch: 1 == Error: 0.004782848060131073
Epoch: 2 == Error: 0.0025183199904859066
Epoch: 3 == Error: 0.0018123439513146877
Epoch: 4 == Error: 0.0014609650243073702
Epoch: 5 == Error: 0.001302198157645762
Epoch: 6 == Error: 0.001175261684693396
Epoch: 7 == Error: 0.0011013821931555867
Epoch: 8 == Error: 0.00105581886600703
Epoch: 9 == Error: 0.0009863674640655518
Epoch: 10 == Error: 0.0009745883871801198
Epoch: 11 == Error: 0.0009395127417519689
Epoch: 12 == Error: 0.0009269587462767959
Epoch: 13 == Error: 0.0009169909753836691
Epoch: 14 == Error: 0.000882455671671778
Epoch: 15 == Error: 0.0008777283364906907
Epoch: 16 == Error: 0.0008869280572980642
Epoch: 17 == Error: 0.0008650723611935973
Epoch: 18 == Error: 0.0008535243105143309
Epoch: 19 == Error: 0.0008724266081117094
Epoch: 20 == Error: 0.0008615754195488989
Epoch: 21 == Error: 0.0008310741395689547
Epoch: 22 == Error: 0.0008509551989845932
Epoch: 23 == Error: 0.0008309109252877533
Epoch: 24 == Error: 0.000849412230309099
```

In [110]:

```python
plt.plot(errors)
plt.title('Error for each Epoch')
plt.ylabel('Error')
plt.xlabel('Epoch')
plt.show()
```



It looks like the error is very low, with possible diminishing returns after epoch 15 or so. It also ran pretty fast, showing its efficiency.

Recommend to Mock User

Let's create a mock user so we can recommend products to it based on the RBM. We will begin by picking 143 for c2's reviews, before making an array of their values. We will then pass it in the input and reconstruct the data with a recommendation score.

In [101]:

```python
# select a user: mock_user_id = 143
mock_user_id = 143
```

In [102]:

```python
# Selecting the input user
inputUser = trX[mock_user_id-1].reshape(1, -1)
inputUser[0:5]
```

Out[102]:

```
array([[0., 0., 0., ..., 0., 0., 0.]])
```

In [103]:

```python
# Feeding in the user and reconstructing the input. use sigmoid
hh0 = tf.nn.sigmoid(tf.matmul(v0, W) + hb)
vv1 = tf.nn.sigmoid(tf.matmul(hh0, tf.transpose(W)) + vb)
feed = sess.run(hh0, feed_dict={ v0: inputUser, W: prv_w, hb: prv_hb})
rec = sess.run(vv1, feed_dict={ hh0: feed, W: prv_w, vb: prv_vb})
```

In [109]:
```
cored_product_df_mock = cleaned.drop_duplicates(subset=['ProductId']) # create df to assign recommendation score
 create column and store RecommendationScore
cored_product_df_mock = scored_product_df_mock.assign(RecommendationScore = rec[0])
 sort values based on RecommendationScore
cored_product_df_mock[['ProductId','RecommendationScore','Summary','Text']].sort_values(["RecommendationScore"], ascending=F
```

Out[109]:

	ProductId	RecommendationScore	Summary	Text
13047	B001FA1K5S	0.018063	Better and Cheaper Than US Version	We got Mexican Nesquik because it was cheaper,...
13046	B002FKG5MA	0.016052	great coffee	There is nothing better then good coffee at a ...
13033	B0011XKHY4	0.015589	airplane cookies! YUM!!	These cookies are so good. I love them. I firs...
3804	B000X2CWTM	0.013651	Real Licorice	I received a box of this for Christmas. It is ...
22788	B00800CDCA	0.012244	Spices for canning	Great product and price if you need large quan...
153	B002HQAXUW	0.012105	Rip off Price	These singles sell for 2.50−3.36 at the st...
12541	B005J7I8FS	0.011919	Delicious wine!! Yummy!	Great with BBQ, we have discovered and focusin...
13815	B0051SZD0S	0.011843	LA VICTORIA GREEN TACO SAUCE	THIS IS "GREEN GOLD"; I DISCOVERED IT WHILE LI...
13767	B001M0ALS8	0.011754	Gordolobo Tea....	This tea is very tasty. I drink one cup of hot...
12890	B004U7QZ4Y	0.011752	Smooth & Awakening!	Tazo Awake Full Leaf Tea is the best black tea...
17570	B0000GH6UQ	0.011405	Heaven!	This is fabulous and it's what we drank when t...
3790	B001L1DYAA	0.011292	best coffee	The Gevalia Breakfast Blend is perhaps the bes...
18452	B0019JRIN8	0.011292	$20 for a little bottle of rice wine? Hello?	Okay, decent drinking wines are $20 for larger...
5012	B000HDKZDC	0.011206	Best cereal bars on the planet	We use these for our daughter for a few reason...
18961	B001H1GUVO	0.011202	Much better than what I've been using.	I've been using another type of ant gel for a ...
8181	B000G7M4U6	0.011164	Great Deal	Ordered these seeds for a recipe that I got fr...
2515	B000RUI0MS	0.011124	Combo Rose Food/Systemic Insecticide	This is a great product, so it's no surprise t...
6131	B000634M5U	0.011092	Perfect Nutrition	This product is perfect for my Cavalier King C...
2871	B001IZI8LE	0.011074	my favorite sugarless flavor	Wrigleys' 5 FLARE sugarless gum is Wrigleys' s...
22790	B004LL7GHO	0.011073	Nutritional Information	Silk Pure Almond® Original Almondmilk Nut...

We are also going to make a df with only user 151's info so we can create a df with the score

In [105]:
```
food_df_mock = cleaned[cleaned['UserID'] == 151]
food_df_mock.head()
```

Out[105]:

	ProductId	ProfileName	Score	Summary	Text	HelpfulnessNumerator	HelpfulnessDenominator	Polarity_Rating	UserID
151	B00374XSVY	Chris	5	Awesome stuff	Works with chicken fish beef or pork. Fast eas...	0	0	Positive	151
637	B000G6RYNE	Chris	4	kettle chips	This kettle chips taste "Good , Crispy & Crunc...	0	0	Positive	151
729	B008BEGP9W	Chris	4	A Surprising Find	I really like the pineapple shortcakes sold he...	0	0	Positive	151
1006	B002XG21MO	Chris	5	A great price!	These are just like the animal crackers we eat...	0	0	Positive	151
3142	B000FDKQCY	Chris	5	Good to use the bread machine again	This product is as good as any that I have eve...	0	0	Positive	151

In [106]:
```
#Merging scored_product_df_mock with food_df_mock by ProductID
merged_df_mock = scored_product_df_mock.merge(food_df_mock, on='ProductId', how='outer')
```

In [115]:
```
merged_df_mock.head()
```

Out[115]:

	ProductId	ProfileName_x	Score_x	Summary_x	Text_x	HelpfulnessNumerator_x	HelpfulnessDenominator_x	Polarity_Rating_x	UserID_x	Recor
0	B001E4KFG0	delmartian	5	Good Quality Dog Food	I have bought several of the Vitality canned d...	1	1	Positive	1	
1	B00813GRG4	dll pa	1	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...	0	0	Negative	2	
2	B000LQOCH0	Natalia Corres "Natalia Corres"	4	"Delight" says it all	This is a confection that has been around a fe...	1	1	Positive	3	
3	B000UA0QIQ	Karl	2	Cough Medicine	If you are looking for the secret ingredient i...	3	3	Negative	4	
4	B006K2ZZ7K	Michael D. Bigham "M. Wassir"	5	Great taffy	Great taffy at a great price. There was a wid...	0	0	Positive	5	

Finally, this last line will show the top 5 products it recommends to user c2 based on highest recommendation score. It will also show the summary and review so we can have an idea of what the product actually is.

In [128]:
```
merged_df_mock[['ProductId','RecommendationScore','Summary_x','Text_x','UserID_x']].sort_values(["RecommendationScore"], as
```

Out[128]:

	ProductId	RecommendationScore	Summary_x	Text_x	UserID_x
1881	B001FA1K5S	0.018063	Better and Cheaper Than US Version	We got Mexican Nesquik because it was cheaper,...	11243
1880	B002FKG5MA	0.016052	great coffee	There is nothing better then good coffee at a ...	11242
1879	B0011XKHY4	0.015589	airplane cookies! YUM!!	These cookies are so good. I love them. I firs...	11230
595	B000X2CWTM	0.013651	Real Licorice	I received a box of this for Christmas. It is ...	3585
2908	B00800CDCA	0.012244	Spices for canning	Great product and price if you need large quan...	18861

Once again, let's make a function that takes index as input and returns recommendation for that userID.

In [129]:
```
def give_recommendations(userID, recs = 5):
    mock_user_id = userID
    inputUser = trX[mock_user_id-1].reshape(1, -1)
    # Feeding in the user and reconstructing the input. use sigmoid
    hh0 = tf.nn.sigmoid(tf.matmul(v0, W) + hb)
    vv1 = tf.nn.sigmoid(tf.matmul(hh0, tf.transpose(W)) + vb)
    feed = sess.run(hh0, feed_dict={ v0: inputUser, W: prv_w, hb: prv_hb})
    rec = sess.run(vv1, feed_dict={ hh0: feed, W: prv_w, vb: prv_vb})
    scored_product_df_mock = cleaned.drop_duplicates(subset=['ProductId']) # create df to assign recommendation score
    # create column and store RecommendationScore
    scored_product_df_mock = scored_product_df_mock.assign(RecommendationScore = rec[0])
    food_df_mock = cleaned[cleaned['UserID'] == userID]
    merged_df_mock = scored_product_df_mock.merge(food_df_mock, on='ProductId', how='outer')
    rec_df = merged_df_mock[['ProductId','RecommendationScore','Summary_x','Text_x','UserID_x']].sort_values(["Recommendati
    print(f'Top {recs} Product Recommendations for UserID: {userID}:')
    return rec_df
```

In [130]:
```
give_recommendations(24,8)
```

```
Top 8 Product Recommendations for UserID: 24:
```

Out[130]:

	ProductId	RecommendationScore	Summary_x	Text_x	UserID_x
958	B003JMH0FY	0.623005	Heavenly!	This is the best quality Chamomile tea I have ...	5716
2447	B001TM3XKW	0.015070	Weruva Bed and Breakfast Canned Dog Food	Although this is very expensive canned dog foo...	15459
2524	B003SC0Q4C	0.012133	Very good stuff	Mmm, The other two reviewers seem to be lacki...	15923
587	B005TAGBVS	0.008702	Really good product!	These bites are 'just enough' for a snack. The...	3514
1320	B0028621BU	0.007732	Overpriced - not 18lb bags!	When I bought this food, I saw the image and p...	8038
1748	B0005YLOH4	0.005585	Bananas, for baby... or for space flight	Anyone searching for stage 3 of gestational ba...	10756
2024	B00374XTQI	0.004994	my own lil store	Received package and was just as I wanted plus...	12321
1610	B0040U9KS4	0.004975	Love this gum.	Very good gum - flavor doesn't last a long tim...	9861

Conclusions

The DL tools at our disposal is constantly growing more powerful and complex, but that does not necessarily mean more computational power in some cases as they can become more efficient as well. For comparison, the simple RNN with LSTM took over an hour to fit with only 8 epochs, while the RBM geared for efficiency did 24 epochs in under 10 minutes. They both had very low error, and were possibly overfit.

If I were to do this over again, I would probably make the score of 3 positive rather than negative, or keep it neutral and used softmax with 3 dense neurons or tanh. Better yet, I should of tuned my hyperparameters with hparams or tensorboard rather than encoding in Kobe Bryant easter eggs.

Overall, I am happy with how well the models performed, but there is definitely room for improvements.

In [ ]: